ORIGINAL SCIENTIFIC PAPER
UDK: 005.521:334.7(497.11)
658.7
DOI:10.5937/EKOPRE1806283D
Date of Receipt: March 29, 2018

Tinde Dobrodolac Šeregelj
University of Novi Sad
Faculty of Economics
Department of Business Informatics and Quantitative Methods, Subotica

Jelena Brdar
University of Novi Sad
Faculty of Economics
Department of Finance, Subotica

BUSINESS ANALYTICS AND FORECASTING FOR SUPPLY CHAIN OPTIMISATION IN SERBIAN COMPANIES

Poslovna analiza i predviđanje u funkciji optimizacije procesa upravljanja lancem snabdevanja u kompanijama Srbije

Abstract

Competition, technological innovations and the intensity of business changes are characteristics of modern-day business operations. Their complexity imposes demands for new policies and approaches in all business areas. In many companies, the procurement department as a business function has become a routine where they continue to maintain long-term business relationships with suppliers and other business partners. This type of policy is becoming unsustainable. The way for a company to survive is to focus on operational efficiency. While conducting the analysis of an oil industry company and its procurement department, we have set an economic model for sales forecasting and procurement plan. Development of computer technology and quantitative methods contributes to the quality of the supply chain. It also opens up new opportunities in business application, while requiring at the same time significant changes in business thinking patterns, especially considering the importance of information, their quantity and availability. In modern business, timely and accurate information and knowledge contained therein are becoming an important business resource and a platform for survival of the company. The aim of this paper is to create a new, i.e. added value, out of the existing information. By applying quantitative methods for business forecasting, we have optimised stock levels. By analysing monthly information on procurement, sales and stock quantities for a single product over a period of 5 years, we have compiled a procurement plan based on business forecasting. With adjusted optimisation we have created an opportunity to release the capital for other purposes and new investments. We achieved the company's goal, and avoided creating excess inventory and missed sales. In our business forecasting, we used Gretl statistical package for data analysis.

Keywords: *business forecasting, inventory management, supply chain management, modelling, optimisation.*

Sažetak

Konkurencija, tehnološke inovacije i intenzitet poslovnih promena su odlike savremenog poslovanja. Njihova kompleksnost postavlja zahteve za novim politikama i pristupima na svim poslovnim područjima. U mnogim kompanijama, nabavka kao poslovna funkcija postala je rutina u kojoj nastavljaju da se održavaju dugogodišnje poslovne veze sa dobavljačima i drugim poslovnim partnerima. Takva poslovna politika postaje neodrživa. Kako bi opstale u tržišnim uslovima, kompanije u fokus svog poslovanja postavljaju operativnu efikasnost. Analizom kompanije naftne industrije i njenog odeljenja nabavke, postavili smo ekonomski model za predviđanje prodaje i plan nabavke. Razvoj kompjuterske tehnologije i kvantitativnih metoda doprinosi kvalitetu rada lanca snabdevanja. Isto tako otvara nove mogućnosti u poslovnoj primeni, zahtevajući značajne promene u poslovnom razmišljanju s obzirom na značaj informacija, njihovu količinu i raspoloživost. U savremenom poslovanju, uz kapital i rad, pravovremene i tačne informacije, znanje koje je sadržano u njima, postaju značajan resurs poslovanja i platforma opstanka kompanije. Cilj ovog rada je da od postojećih informacija stvorimo novu – dodatnu vrednost. Primenom kvantitativnih metoda za predviđanje prodaje izvršena je optimizacija zaliha. Analizom mesečnih informacija o nabavci, prodaji i količini na zalihama jednog proizvoda (početno stanje) u vremenskom periodu za 5 godina, sastavlja se plan nabavke na osnovu ekonomskog predviđanja prodaje. Optimizacijom smo stvorili mogućnost za oslobađanje i primenu kapitala za druge namene i nove investicije. Ostvarili smo cilj kompanije i izbegli stvaranje prekomernih zaliha i propuštenih prodaja. U radu za ekonomska predviđanja prodaje koristili smo statistički paket za analizu podataka Gretl.

Ključne reči: *ekonomsko predviđanje, zalihe, optimizacija, upravljanje procesom nabavke, prodaja.*

Introduction

Business environment of companies on the market and the characteristics of modern business companies set serious competitive objectives with the aim of preserving and creating profit. In the past, the area of inventory management was often neglected, but today it is gaining an increasing importance. Inventory management is a key process of supply chain management, which implies a common understanding of all processes within the company, and represents the link between the manufacturer and customer demand. By sharing this information, we come to the objective of supply chain management, which is reflected in the control of optimal inventory levels that exist among all the organizations in the chain. With proper optimisation capital is released for other purposes and new investments. Computer technology contributes to the quality of the supply chain. Moreover, it opens up new opportunities in business applications, requiring significant changes in business thinking with regard to the importance of information, the quantity and availability. In modern business, alongside capital and labour, timely and accurate information and the knowledge contained therein are becoming an important business resource and a platform for survival of the company. The aim of this paper is to create a new, i.e. added value out of existing information. Through analysis of monthly information on acquisition, sales and the amount of stock of a product (baseline) over a period of 5 years, the acquisition plan is drawn up on the basis of economic forecasting sales. The forecasting we performed was based on two samples: the shorter sample, with data for the last 5 months, and the longer sample data, with sales forecast for the next 5 months. In the economic forecasts of sales, we used the statistical package for data analysis Gretl (Gretl software package).

Overview of relevant literature

The scientific area of the process of inventory management (Supply Chain Management) is becoming increasingly important, as evidenced by numerous scientific papers in this field. In his work, Bugar [3] points out that an effective inventory management is the key factor in the efficiency of the organization. The manager's task is, in addition to defining the qualitative aspect of the stock, to ensure that a large part thereof be considered in terms of quantitative analysis as well. The success of an organization can be achieved only if the strategy combines cost strategy (importance is attached to quantitative indicators optimisation) and product diversification strategy (emphasis is placed on product quality). In a scientific paper, the authors Szymszal et al. [15] presented a method for optimising inventory management in terms of the size of the acquisition. As an optimisation tool they used MS Excel computational tables with functions for different modules. As the authors pointed out, successful optimisation requires quantitative analysis as well. Based on the research of Lapinskas [11], we became acquainted with the significance of time series and statistical indicators. In their paper, Kish et al. [10] described the basic elements of forecasting demand. They pointed out that the demand forecast is the basis for planning the logistics activities of the company, where capacities and stocks belong. Historical data on the demand for a product are an essential element of forecasting [12]. Good forecasts require that companies have a historical database, and therefore big data have a huge importance in business. In their scientific paper, Wang et al. [19] realise the importance of this area, because big data can provide unique insights into, inter alia, market trends, customers' buying patterns and maintenance cycles, as well as into ways of lowering costs and enabling more targeted business decisions. As an area that provides many opportunities, there are different possibilities of applied research and analysis of big data. In her article, Sanders [14] examines how leading companies use big data analytics to drive their supply chains and offers a framework for implementation. There are many challenges and opportunities in combining application of operational methods in the analysis of large data pointed out in the paper of Hazen et al. [9]. Data and statistical analyses provide new opportunities for competitive advantage by extracting huge value from large amounts of data [8]. Savings in capital and time are just some of the factors that are the basis of creating a method for analysing and forecasting in supply chain area [17]. Dobrodolac described the importance of forecasting to support management in her work [6]. Based on the research of many scholars in this field, we see that the goal of our work is important for improving the business operations of companies in this field. New business conditions are characterized by complex problems, the uncertainty of the situation and because of that, planning and forecasting should provide better results in achieving the objectives of an organization. Econometric models can be used for forecasting, as they provide planning and selection of strategic goals. Ideal forecast is achieved by combining two types of methods: a group of methods based on intuition and subjective assessments, and a group of methods based on statistical and mathematical techniques, including econometric models. We needed all this theoretical knowledge to make our model for forecasting of sales, and optimise and improve inventory management modes. Our starting hypothesis is that, through application of quantitative methods in forecasting sales, better inventory can be realized in acquisition plans in comparison to unplanned (accidental) procurement.

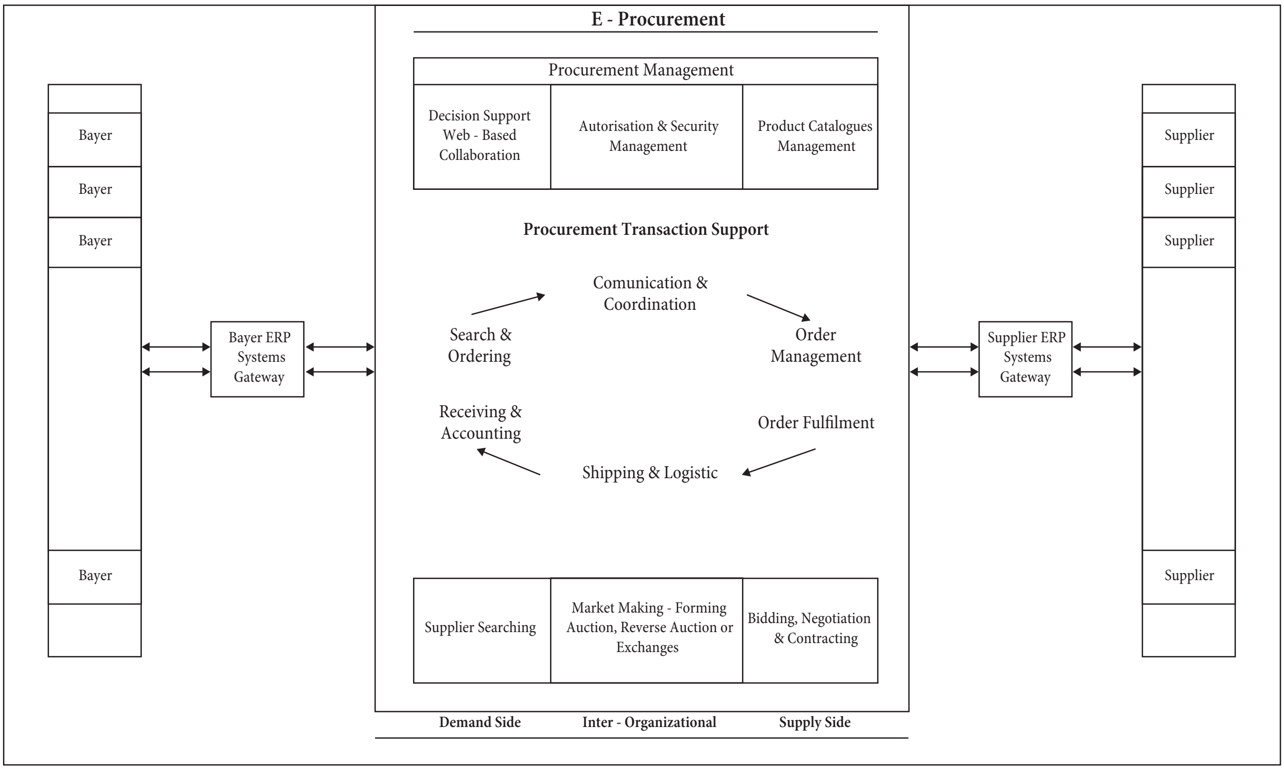
Supply chain management

Supply chain management (SCM) [7] is becoming a major component of competitive strategy for improving organizational productivity and profitability. Literature dealing with strategies and technologies for efficient supply chain management is rather extensive. Lately, this important area attracts more and more researchers and analysts. According to the definition, supply chains are linear systems for which the raw material is the input, and finished product in the hands of customers is the output. Usually the companies in this process produce large amounts of stocks in defence of the variability and volatility of demand. Due to major changes, such an approach proved to be inadequate. The introduction of supply chain management aims to reduce the cost of inventory with more accurate forecasting of requirements and needs of the participants in the process. Establishing cooperation and exchange of information between suppliers and enterprises are important because working in this way significantly reduces or eliminates the safety stock. Electronic data interchange (EDI) provides a good connection between the customer's database and the vendor's database. By accessing the database, vendors can see the information on deliveries, sale, and level of inventories. The buyer will form the electronic exchange of data with only a few suppliers. Because of this, the trend for companies is to reduce the number of suppliers in collaboration. Large companies are characterized by abundance of data and knowledge contained therein. The administration company analysed in this paper (Naftna industrija Srbije - Oil Industry of Serbia) belongs to a group of large companies. Such companies develop Enterprise Resource Planning (ERP) systems [1] for financing, forecasting, monitoring of orders, sales analysis, and quality control. The starting point of the analysis in this paper is a time series of data on the movement of stock to a sales facility operated. By predicting sales trends, we have tried to make the acquisition plan for the future. Figure 1 is an example of an advanced supply chain management system [2].

Analysis of time series in forecasting inventory sales

Time series analysis is a quantitative method, commonly used in forecasts. Forecasting is present in studies of numerous phenomena and effects in order to estimate the future values. An important assumption of most forecasting methods is that the patterns of the past are going to repeat in the future. For a good assessment it is necessary to have high-quality information. Chronologically arranged historical data represent the time series. Through the analysis of time series of historical data series of sales of the products by a single facility for a period of 5 years (e.g. in operation), we have created a model to predict sales for the past and forthcoming 5 months. Analyses of the data observed characteristics such as the development of phenomena in time unit. By forecasting time series we mean the use of models for forecasting of future values on the basis of autonomous movement of the phenomenon. Models for time series data may have a different form, and this paper presents a statistical model for forecasting (Gretl software package).

Figure 1: Improving e-procurement in supply chain through web technologies



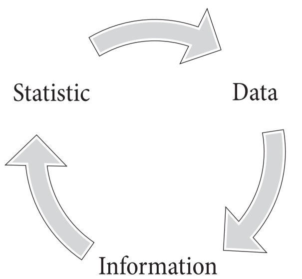
Source: Alor-Hernandez, G., Aguilar-Laserre, A. A., Cortes-Robles, G., & Sanchez-Ramirez, C. (2011). Improving e-procurement in supply chain through web technologies.

For many organizations, investment in the construction of a high-quality prediction model has a long-term impact on profitability, customer service, productivity and similar indicators. A good combination of statistical analysis and forecasting is the base for preventing problems such as lack of inventory, missing deadlines, lost sales, lost customers, and failure of strategic opportunities. Figure 2 represents the importance of statistics in the transformation of data into information, that is, knowledge.

We performed statistical analysis, stability testing and foresight in the work by assessing some of the most important statistical indicators:

The coefficient of determination R^2:

Figure 2: The importance of statistics in data analysis



Source: View of the author of the research paper, 2018.

$$R^2 = 1 - \frac{SSR}{SST}$$

$$SST = \sum_{i=1}^{N} \left(Y_i - \overline{Y}\right)^2 \qquad (1)$$

$$0 \le R^2 \le 1$$

The coefficient of determination is the proportion of the variation from the sample interpreted with linear regression relationship. It represents the ratio of the interpreted and total deviation. The height of the coefficient of determination shows the representativeness of the model – a model which is a more representative value is closer to 1. The coefficient of determination represents the percentage of the total variation phenomena that can be explained by the influence of the trend (tendency of development in time), and the other part is the impact by the model of omitted factors.

Adjusted coefficient of determination R^2:

$$\overline{R}^2 = 1 - \frac{SSR/(N-k)}{SST/(N-1)} \qquad (2)$$

The adjusted coefficient of determination (Adjusted - R-squared) adjusts the coefficient of determination in order to obtain indicators that will not unduly rise with the increase in the number of explanatory variables. The adjusted coefficient of determination is always less than the ordinary coefficient of determination. The coefficients are equal only to a simple model without a free member.

Information criteria:

Akaike information criterion (AIC)

$$AIC = exp\ \left(2k / N\right)\frac{SSR}{N} \tag{3}$$

(Schwarz information criterion - SIC)

$$SIC = N^{k/N}\ \frac{SSR}{N} \tag{4}$$

(Hannan – Quinn information criterion - HQC)

$$HQC = n \ln \frac{SSR}{n} + 2k \,\mathrm{loglog}n \tag{5}$$

Information criteria [18] are used in the selection of the optimum number of parameters in the econometric model. They contain two components: a component that is in the function of the unexplained variance of the dependent variable models, and a component which „punishes" the loss of the number of degrees of freedom due to the addition of new parameters (the so-called criminal component). An important group of criteria consists of information criteria: Akaike (AIC) and Schwarz information criterion (SIC). AIC was originally known as the Information Criterion (Akaike, 1973). Both criteria calculate the residual sum of squares, taking into account the introduction of additional parameters in the model. It is believed that the model is better for forecasting if the calculated value of AIC and SIC have smaller values. One of the ways for evaluation of criteria that is used for selection pertains to consistency. It can be shown that the AIC is an inconsistent criterion, which means that it will not choose the right model when the real model is among those that are considered likely to be closer to the sample as unit is increased. It turns out that the SIC is consistent, but not asymptotically efficient. Several variations and extensions of these information criteria were therefore created.

Many statistical packages allow the selection of a suitable model through these criteria. Specifically, we conducted an assessment of the quality of sales forecasts through analysis of some of the criteria listed in the following part of the paper.

Empirical research

Having outlined the importance of the process of inventory management, and analysed the time series data and the importance of statistical analysis, we move to research work. The goal that we want to achieve is to reduce the gap between the purchase and sale of the stock. The hypothesis that we want to prove is that economic forecasting is in the function of optimisation of inventory levels in relation to unplanned purchases. The analysis included a time series of 55 months: data on monthly acquisition, sales, initial and final state of stock of Fanta beverage (Table 1).

The research started by observing the relation between the current acquisition and sales and the sum of opening balances and purchases in relation to the sale. Figure 3 shows diagrams of the time series for the initial state, the purchase and sale over a period of 5 years.

Interdependence between observed phenomena of procurement and sales and the total amounts of inventory and sale is easiest to observe based on the dispersion diagram (Figures 4 and 5).

By observing Figure 3a we cannot conclude that there is interdependence between the procurement and sales. Based on Figure 3b, we can assume that there is interdependence in the behavioural development of the total stocks (acquisitions and initial state) and sales, but also that the gap is huge and thus creates additional costs for the company. Based on Figures 4 and 5, it can be concluded that there is interdependence between the two phenomena. Unplanned purchases drive capital spending to non-profitable purposes, making it thus captured by the impossibility of being placed into the investments that are profitable for the company. The aim of the further step in the research is forecasting demand, i.e., sales of stocks of products.

The next phase of the research is to predict demand, that is, sales stocks of products, comprising the following steps:

1. To define sample time series data and trend line (Gretl package)
2. To form a trend model and periodicity of the phenomenon movement
3. To carry out forecast within the sample data and assess the quality of forecasts (01.01.2015-01.05.2015)
4. To carry out forecast outside sample data (01.06.2015 - 01.10.2015)

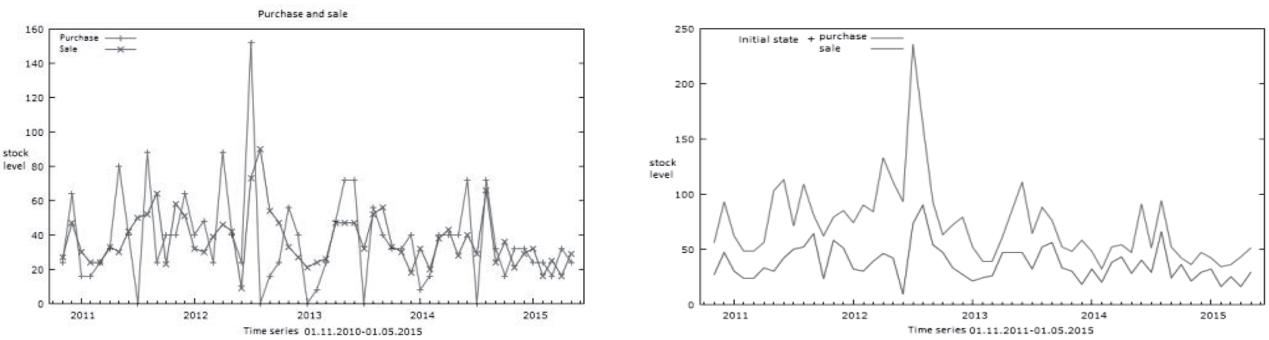
Figure 6 presents the movement of sales of juice and a trend line for the entire data set – a sample of 55 months.

Based on sale trends of juice, we can see that there is a certain dynamic in the movement, and that sales are

Table 1: Time series data: purchasing, sales, initial and final state

Inventory/time	Initial state	Purchase	Sale	Final state	Inventory/ time	Initial state	Purchase	Sale	Final state
11/2010	32	24	27	29	03/2013	15	24	26	13
12/2010	29	64	47	46	04/2013	13	48	47	14
01/2011	46	16	30	32	05/2013	14	72	47	39
02/2011	32	16	24	24	06/2013	39	72	47	64
03/2011	24	24	24	24	07/2013	64	0	32	32
04/2011	24	32	33	23	08/2013	32	56	52	36
05/2011	23	80	30	73	09/2013	36	40	56	20
06/2011	73	40	42	71	10/2013	20	32	33	16
07/2011	71	0	50	21	11/2013	16	32	30	18
08/2011	21	88	52	57	12/2013	18	40	18	40
09/2011	57	24	64	22	01/2014	40	8	32	16
10/2011	22	40	23	39	02/2014	16	16	20	12
11/2011	39	40	58	21	03/2014	12	40	38	14
12/2012	21	64	51	34	04/2014	14	40	43	7
01/2012	34	40	32	42	05/2014	7	40	28	19
02/2012	42	48	30	60	06/2014	19	72	40	51
03/2012	60	24	39	45	07/2014	51	0	29	22
04/2012	45	88	46	71	08/2014	22	72	66	20
05/2012	71	40	42	69	09/2014	20	32	24	26
06/2012	69	24	9	84	10/2014	26	16	36	4
07/2012	84	152	73	163	11/2014	4	32	21	15
08/2012	163	0	90	77	12/2014	15	32	29	18
09/2012	77	16	54	39	01/2015	18	24	32	10
10/2012	39	24	47	16	02/2015	10	24	16	20
11/2012	16	56	33	39	03/2015	20	16	25	11
12/2012	39	40	27	52	04/2015	11	32	16	27
01/2013	52	0	21	31	05/2015	27	24	29	22
02/2013	31	8	24	15	06-10	X	Forecast	X	X

Figure 3: Diagram of time series (01.11.2010 – 01.05.2015)



a) procurement and sales / data on the amount of procurement and sales for the period of 5 years

b) initial state + procurement and sales data on the overall state of the stock

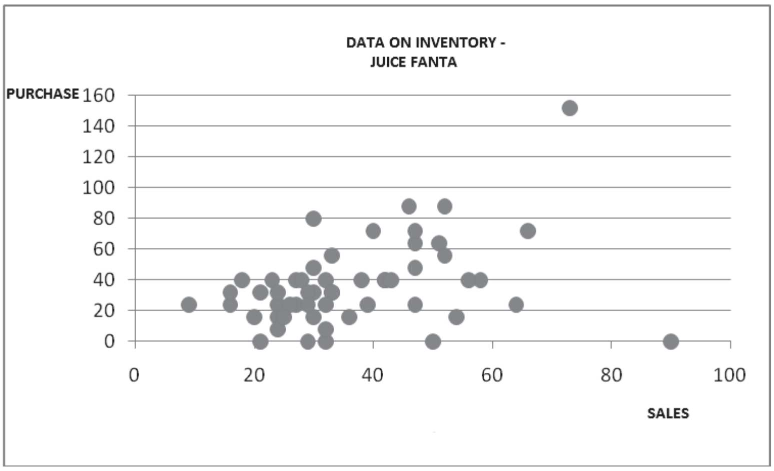
Source: View of the author of the research paper, 2018.

higher in the summer period, while decreasing in the winter period. According to the trend line, we see that the sales of goods are moving in the slightly descending direction. This information is also of importance to us while drawing up plans for the purchase in the future.

The next step in the research is to add time trend variable and temporal periodicity – dummies in Gretl statistical package.

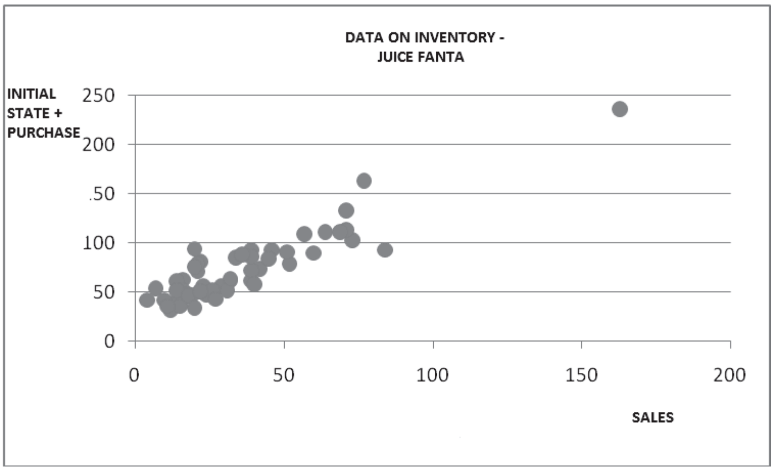
The first prediction we performed was for the last 5 months in the sample (01.01.2015 -01.05.2015).

Figure 4: Dispersion diagram of Supply – Sales



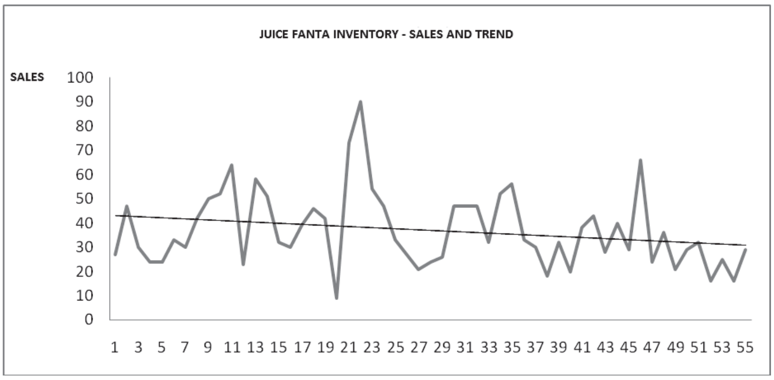
Source: View of the author of the research paper, 2018.

Figure 5: Dispersion diagram of Total inventories - Sales



Source: View of the author of the research paper, 2018.

Figure 6: Time series of sold juice inventory and trend line (01.11.2010-01.05.2015)



Source: View of the author of the research paper, 2018.

Statistical results for the first model

Model 1: OLS, using observations 2010:11-2014: 12 (T = 50)

Dependent variable: sales of juice for a truncated data sample

Table 2: Statistical results for Model 1

	Coefficient	Std. Error	T-ratio	P-value
Const	33.0375	7.00264	4.7179	0.00003
Time	-0.204167	0.128689	-1.5865	0.12113
dm2	-4.04583	9.13695	-0.4428	0.66049
dm3	3.40833	9.13966	0.3729	0.71134
dm4	14.1125	9.14419	1.5433	0.13126
dm5	8.81667	9.15053	0.9635	0.34154
dm6	6.77083	9.15867	0.7393	0.46440
dm7	18.475	9.16861	2.0150	0.05121
dm8	37.6792	9.18034	4.1043	0.00021
dm9	22.3833	9.19386	2.4346	0.01985
dm10	7.8375	9.20916	0.8511	0.40021
dm11	5.86667	8.68248	0.6757	0.50344
dm12	6.67083	8.69106	0.7676	0.44762

Table 3: Statistical results for Model 1

Mean dependent variable	38.32000	S.D. dependent variable	15.54643
Sum squared residuals	6176.575	S.E. of regression	12.92031
R-squared	0.478457	Adjusted R-squared	0.309307
F(12, 37)	2.828608	P-value (F)	0.007540
Log-likelihood	-191.3593	Akaike criterion	408.7187
Schwarz criterion	433.5750	Hannan-Quinn	418.1841
Rho	-0.096759	Durbin-Watson	2.171306

Statistical results for the second model

The second prediction we performed was for the next 5 months in the sample (01.05.2015-01.10.2015).

Model 2: OLS, using observations 2010: 11-2015: 05 (T = 55)

Dependent variable: juice sales for the entire sample of data

The first model is with the shortened time series data (T = 50), without the last 5 months. The second model includes the entire set of data (T = 55). The second model shows greater stability (higher values of the second model for determination coefficients). With the extension of the time series data we are gaining a more stable model, and therefore a greater predictive power of the model. Out of information criteria, the Akaike has the lowest value out of the three observed, both for the first and second model. F-statistics is used to test the stability of parameters and reach a conclusion about the predictive power of the model. If F* <F (α, n2, n1-k), then we conclude that the predictive power of the model is satisfactory. For the calculation of F*, we use the formula:

$$F^* = \frac{\frac{\sum ei^2 - \sum (ei)^2}{n_2}}{\frac{\sum (ei)^2}{n_1 - k}} = \frac{\frac{3.45 - 2.83}{5}}{\frac{2.83}{50 - 12}} = 1.67$$

$$F^* = 1.673931 < F^1(12, 37) = 2.828608 < F^2(12, 42) = 3.451620 \tag{6}$$

Table 4: Statistical results for Model 2

	Coefficient	Std. Error	T-ratio	P-value
Const	35.6408	6.29356	5.6631	<0.00001
Time	-0.23114	0.106917	-2.1619	0.03637
dm2	-6.36886	7.90966	-0.8052	0.42524
dm3	1.46228	7.91183	0.1848	0.85426
dm4	8.29342	7.91544	1.0478	0.30074
dm5	6.72456	7.92049	0.8490	0.40069
dm6	4.86886	8.38938	0.5804	0.56477
dm7	16.6	8.38869	1.9789	0.05441
dm8	35.8311	8.38938	4.2710	0.00011
dm9	20.5623	8.39142	2.4504	0.01852
dm10	6.04342	8.39482	0.7199	0.47557
dm11	3.93772	7.91183	0.4977	0.62129
dm12	4.76886	7.90966	0.6029	0.54981

Table 5: Statistical results for Model 2

Mean dependent variable	36.98182	S.D. dependent variable	15.54264
Sum squared residuals	6567.884	S.E. of regression	12.50513
R-squared	0.496520	Adjusted R-squared	0.352669
F(12, 42)	3.451620	P-value (F)	0.001398
Log-likelihood	-209.5635	Akaike criterion	445.1270
Schwarz criterion	471.2223	Hannan-Quinn	455.2183
Rho	-0.091602	Durbin-Watson	2.159915

Table 6: Statistical results for Model 1 and Model 2

	Model 1	Model 2
R^2	0.478457	0.496520
$\bar{R}^2$	0.309307	0.352669
Akaike criterion	408.7187	445.1270
Schwarz criterion	433.5750	471.2223
Hannan-Quinn criterion	418.1841	455.2183
Sum squared resid.	6176.575	6567.884
F – test	F(12, 37) = 2.828608	F(12, 42) = 3.451620

According to the statistics for testing the predictive power, we conclude a satisfactory predictive power of the models 1 and 2.

The next step in the analysis is the use of a statistical package for the prediction. The results of forecasts for the next 5 months (01.01.2015-01.05.2015) are presented in Figures 7 and 8.

The result of sales prediction:

For the 95% confidence interval, t (37, 0.025) = 2.026

The results obtained for prediction are satisfactory. For the first and fourth month, there was the deviation of actual and predicted value. Based on the behaviour from the past, when the winter sales were smaller, the model learned that the value should be lower; for the month 4, the model gave a higher score as compared to the actual, because the previous 4 years of sales in those months were higher. In addition to the analysis of historical series, in subsequent studies we will look at the new information, data on weather conditions, the manufacturer and distributor of products and other external parameters that may have an impact on the behaviour of sales. Prediction for the second, third, and fifth month approximates the actual value of sales in that period.

Table 7: The prediction result for shorter sales time series in sample

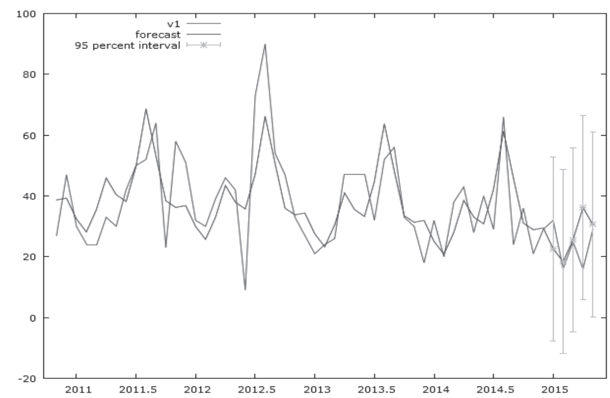
Period of time	Actual	Forecast	Standard error	95% interval
2015:01	32.0000	22.6250	14.9524	(-7.67135, 52.9214)
2015:02	16.0000	18.3750	14.9524	(-11.9214, 48.6714)
2015:03	25.0000	25.6250	14.9524	(-4.67135, 55.9214)
2015:04	16.0000	36.1250	14.9524	(5.82865, 66.4214)
2015:05	29.0000	30.6250	14.9524	(0.328650, 60.9214)

The second test is predicting outside the sample for the next 5 months (01.06.2015 - 01.10.2015) on the entire set of data (time series of 55 months). Forecast results are presented in Figures 9 and 10.

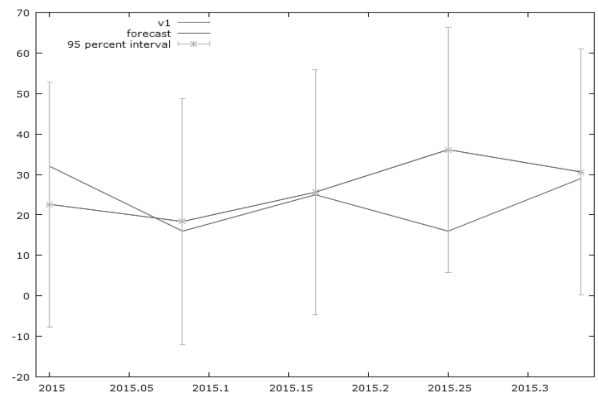
The result of sales prediction:

For the 95% confidence interval, t (42, 0.025) = 2.018

Figures 7 and 8: Prediction and results



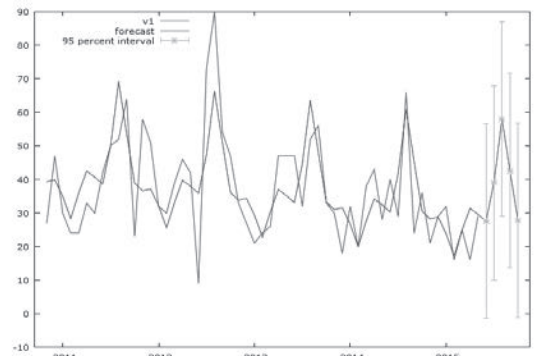
a) Prediction of the sample data



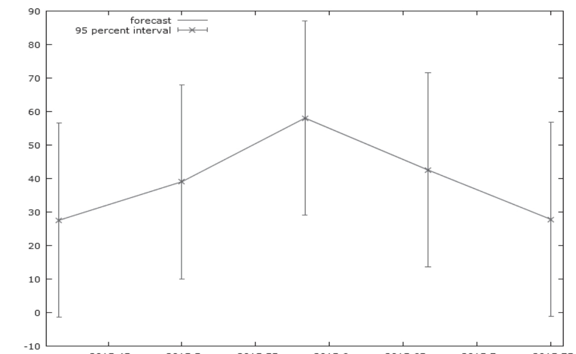
b) The result of prediction (01.01.2015 - 01.05.2015)

Source: View of the author of the research paper, 2018.

Figures 9 and 10: Prediction outside the sample and results



a) Prediction outside the sample



b) Prediction results (01.06.2015 - 01.10.2015)

Source: View of the author of the research paper, 2018.

Table 8: The prediction result for longer sales time series in the sample

Period of time	Actual	Forecast	Standard error	95% interval
2015:06	Undefined	27.5658	14.3444	(-1.38231, 56.5139)
2015:07	Undefined	39.0658	14.3444	(10.1177, 68.0139)
2015:08	Undefined	58.0658	14.3444	(29.1177, 87.0139)
2015:09	Undefined	42.5658	14.3444	(13.6177, 71.5139)
2015:10	Undefined	27.8158	14.3444	(-1.13231, 56.7639)

Results of forecasts for the next period 01.06.2015-01.10.2015 make sense, given that sales in previous periods had this trend, i.e. sales growth in the summer months. It remains to test the model with actual results of the expiration of the period. As it is highlighted, forecasting is a complex area, and for a better and more realistic result it is necessary, in addition to a series of historical data, to consider other indicators as well. With this research for sale, we could make an acquisition plan for the future and thus reduce the gap that existed at the beginning of the analysis (Figures 3a and 3b) and fulfil the initial goal of optimizing stock levels in the company and investments of capital in profitable purposes.

Conclusion

The area of supply chain planning and forecasting has experienced tremendous advances over the last 50 years. There have been significant methodological developments, such as the emergence of system dynamics, control theory and statistical forecasting methods. These developments have been mirrored by new software applications, reflecting their importance in practical situations. The pace of technological change brings the era of change for the companies as well. Companies that spent their funds uneconomically will not be able to be active market players for long. This is precisely the reason for using wealth and knowledge that quantitative analyses contain. The example analysed in the paper described how we can make savings in procurement. By applying quantitative methods and statistical programs for forecasting, we have shown that the procurement can be optimised. The results of statistical indicators for shorter and longer model gave results with which we demonstrated the stability of the model and satisfactorily predictive power. With longer sample data, the model shows greater stability. By predicting sales, we managed to reduce the gap between the procurement and sales and optimise inventory levels. The research confirmed the initial hypothesis that the results of forecasting sales using statistical methods are better than the previous unplanned procurement in the company.

Given that supply chain management is one of significant management tasks, the solution to this problem results in increase of competitive ability and sustainability of companies over a longer time interval, even in the new business setting. To achieve an increase in the efficiency of the supply chain with the least possible resource input, it is necessary to apply quantitative method in inventory management. Application of quantitative methods in inventory management results in making better decisions than in the case of using only intuitive methods.

The main contribution of this paper is a presentation of methodology for inventory level optimisation and possibility of investing capital in more profitable purposes, thus enhancing the overall efficiency of business. The research section of the paper looks into setting a sales forecasting model within a supply chain. As the environment changes rapidly, by testing the stability of parameters, we verified with certain probability that the forecasting error equals zero. We reached a conclusion that the model's predictive power is satisfactory. As higher stability of historical data produces more certain forecasts, the assessed model can be used for higher quality of decision- making. The main limitation of this model is that we did not take into account the seasonal character of the observed phenomenon. Future research should include this characteristic as well.

To maximize benefit, companies should embrace a data-driven approach because data is at the core of every supply chain transaction and is fundamental to product, information, and financial flow optimisation. Plans for future surveys are going to be included in the analysis, and other types of stock of companies to make sales forecasts. Also, we can make plans not only for the office building, but also for the rest, by observing objects according to size, geographical location, traffic, making clusters and similar objects grouped in order to facilitate forecasts. In addition to the historical data analysis, we can include other information that may be relevant depending on the type of stocks. Our goal is to optimise inventories at the level of the whole company with the help of the explained model of economic forecasting.

References

1. Ash, C. G., & Burn, J. M. (2003). A strategic framework for the management of ERP enabled e-business change. *European Journal of Operational Research*, *146*(2), 374-387.
2. Alor-Hernandez, G., Aguilar-Laserre, A. A., Cortes-Robles, G., & Sanchez-Ramirez, C. (2011). Improving e-procurement in supply chain through web technologies: The HYDRA approach. In *Supply Chain Management-New Perspectives*, *32*, 711-737.
3. Bugar, D. (2008). Inventories in function of the organization efficiency. *School of Business*, *2*,131-134.
4. Chan, H. K., Subramanian, N., & Abdulrahman, M. D. A. (2016). Supply chain management in the big data era. *IGI Global*, *3*, 25-49.
5. Dangwal, P. (2014). A statistical way of decision support system. *International Journal of Technical Research and Applications*, *2*(3), 129-141.
6. Dobrodolac, T. (2011). Forecasting by econometric models as support to management. *Perspectives of*
7. *Innovations, Economics and Business*, *7*(1), 72-77.
8. Fredendall, L. D., & Hill, E. (2016). *Basics of supply chain management*. Boca Raton: CRC Press, Teylor&Francis Group.
9. Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business*
10. *Research*, *70*, 308-317.
11. Hazen, B. T., Skipper, J. B., Boone, C. A., & Hill, R. R. (2016). Back in business: Operations research in support of big data analytics for operations and supply chain management. *Annals of Operations Research*, 1-11.
12. Kiš, T., Čileg, M., Dobrodolac, Š. T., Radovanov, B., & Marcikić, A. (2014). Ekonomsko predivđanje, Bečej: Proleter.
13. Lapinskas, R. (2008). *Time series analysis*. Vilnius University.
14. Özdilek, Ü. (2016). Common essentials in a demand-supply allocation model for regional development forecasting. *Journal of Urban Planning and Development*, *142*(4), 95-108.
15. Ross, D. F. (2016). *Introduction to supply chain management technologies*. Boca Raton: CRC Press, Teylor&Francis Group.
16. Sanders, N. R. (2016). How to use big data to drive your supply chain. *California Management Review*, *58*(3), 26-48.
17. Szymszal, J., Gajdzik, B., Piątkowski, J., & Kliś, J. (2012). Optimisation of inventory management in foundry in terms of an economic order quantity. *Metalurgija*, *51*(2), 281-284.
18. Stefanovic, N. (2014). Proactive supply chain performance management with predictive analytics. *The Scientific World Journal*, *4*, 55-77.
19. Shen, B., & Chan, H. L. (2017). Forecast information sharing for managing supply chains in the big data era: Recent development and future research. *Asia-Pacific Journal of Operational Research*, *34*(01), 1-26.
20. Van Fraassen, B. C., & Halpern, J. Y. (2016). Updating probability: tracking statistics as criterion. *The British Journal for the Philosophy of Science*, *68*(3), 725-743.
21. Wang, G., Gunasekaran, A., Ngai, E. W., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, *176*, 98-110.
22. Gretl, version 1.10.1, downloaded on 10.01.2016 from http://gretl.sourceforge.net/win32/.

Tinde Dobrodolac Šeregelj

has been working at the Faculty of Economics in Subotica since 1983. Currently she holds the position of Assistant Professor for the scientific field of quantitative methods in economics. She obtained her PhD in 2008 with doctoral dissertation entitled „Econometric Analysis of Demand of Agricultural Food Products in Vojvodina". At present, she teaches courses in Mathematics for Economists, Statistics, Quantitative Methods in Economics and Prediction and Forecasting. She authored numerous scientific papers (more than 60) and published four books (*The Application of Statistics in Economics, Statistics in Agriculture, Statistics for Example, Economic Forecasting*).

Jelena Brdar

defended her master's thesis entitled „The Strategy of Investing in Securities on Secondary Financial Markets". She was a scholar of the Fund for Young Talents in the 2012-2013 period. That same year she started her PhD studies at the Department of Finance of the Faculty of Economics. Areas of research dedicated to her previous scientific research include investment in financial markets and stock exchanges, data mining, financial mathematics and economic forecasting. The results of her scientific research were published in 11 scientific reports. In addition to her scientific work, Jelena also spent five years in the business sector - in the Serbian oil company NIS and is currently employed at PepsiCo's at the position of planning and forecasting analyst.